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A NOVEL INTERPRETATION OF THE POLSAR COHERENCY MATRIX DATA

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ABSTRACT

Cloude-Pottier incoherent target decomposition (ICTD) and Touzi ICTD has been widely applied as a popular approach to interpret the scattering characteristics of a target in polarimetric synthetic aperture radar (PolSAR) data processing. However, they have a common drawback, i.e. proliferation of parameters (PoP) is unavoidable. Paladini *et al*. solved this problem by developing an orientation-invariant ICTD based on the coherency matrix under circular polarization basis. As an alternative to Paladini decomposition, we proposed a novel ICTD based on the frequently used coherency matrix under linear polarization basis. The proposed method can also avoid the problem of PoP, and avoid the ambiguity of alpha angle of Paladini decomposition as well. Real PolSAR data is processed to validate the proposed decomposition.

***Index Terms*—** Coherency matrix, ICTD, PolSAR, target decomposition

1. INTRODUCTION

Target decomposition is a popular way for target understanding in polarimetric synthetic aperture radar (PolSAR) data processing. Target decomposition includes two categories: coherent target decomposition (CTD) based on the scattering matrix and incoherent target decomposition (ICTD) based on the second order statistical coherency matrix or covariance matrix. As the incoherent scattering is general in real situation, ICTD has attracted much attention. ICTD originates from Huynen decomposition [1]. Due to its preference for symmetry and regularity, Huynen decomposition has not been widely applied [2]. Nowadays, the hotspots of ICTD are eigen-decomposition [3-5] and model-based decomposition [6-13].

Eigen-decomposition was pioneered by Cloude and Pottier [3], which was criticized by Huynen that serious proliferation of parameters (PoP) was generated [14]. Touzi also designed a successful ICTD based on his target scattering vector model (TSVM) [4], but PoP was still a problem. Paladini *et al*. proposed a novel ICTD of the coherency matrix under circular polarization basis, and successfully solved the problem of PoP [5]. A potential limitation of Paladini decomposition is that its alpha angle is identical to Cloude-Pottier alpha angle, while the helix angle is mixed in the alpha angle.

For model-based decomposition, the three-component decomposition or four-component decomposition is clear in physical meaning, and easy to be implemented [6-9]. However, their disadvantage is information loss. Chen *et al*. proposed a novel model-based decomposition with separate orientation angle for odd- and double-bounce models [10], but we think the helix component should be modeled as the asymmetry of odd- and even-bounce scatterers, not as an independent scattering component. Van Zyl *et al*., Cui *et al*., and Wang *et al*. proposed nonnegative eigen-decomposition [11-13], but the interpretation of scattering mechanisms is partially based on eigen-decomposition, not on scattering models.

As an alternative to Paladini decomposition, our ICTD which bases on the coherency matrix under linear polarization basis also avoids PoP, and also avoids the alpha angle ambiguity of Paladini ICTD.

2. MATRIX DEFINITIONS

For coherent scattering, the full polarimetric scattering information is contained in the scattering matrix

$$S=\begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \quad (1)$$

where the subscript *HV* denotes vertical polarization transmission and horizontal polarization reception. Two of frequently used scattering vectors are the scattering vector k_P in Pauli basis and the scattering vector k_C in circular polarization basis

$$k_P=\frac{1}{\sqrt{2}}\left[S_{HH}+S_{VV} \quad S_{HH}-S_{VV} \quad 2S_{HV}\right]^t \quad (2)$$

$$k_C=\left[S_{LL} \quad \sqrt{2}S_{LL_\perp} \quad S_{L_\perp L_\perp}\right]^t \quad (3)$$

where the superscript t denotes matrix transposition, and the subscripts L and $L_\perp$ denote left circular polarization and left orthogonal polarization.

For incoherent scattering, the full polarimetric information is contained in the second order statistical coherency matrix T in linear polarization basis or coherency matrix G in circular polarization basis

$$T=\left\langle k_P \cdot k_P^\dagger \right\rangle \quad (4)$$

$$G=\left\langle k_C \cdot k_C^\dagger \right\rangle \quad (5)$$

where $\langle\cdot\rangle$ denotes time average or spatial average, and the superscript † denotes complex conjugation and transposition. Both T and G have nine degrees of freedom (DoFs).

The Cloude-Pottier, Touzi, and the proposed ICTDs are based on the coherency matrix T, while the Paladini ICTD is based on the coherency matrix G

3. THE PROPOSED ICTD

The proposed ICTD is based on eigen-decomposition of the coherency matrix T

$$T=U\Lambda U^\dagger \quad (6)$$

where Λ is the diagonal matrix whose diagonal elements are the eigenvalues λ_1, λ_2, and λ_3, with $\lambda_1\geq\lambda_2\geq\lambda_3$ assumed, and U is comprised of three columns of eigenvectors k_1, k_2, and k_3.

The matrix U is modelled by the multiplication of six unitary transformation matrices, and the DoF of each unitary transformation matrix is one

$$U=[k_1 \quad k_2 \quad k_3]=\prod_{i=1}^{6} SU(w_i) \quad (7)$$

In the following subsections we will detail the models of the matrices Λ and U.

3.1. Information extraction from the matrix Λ

The matrix Λ has the form $\Lambda=\mathrm{diag}(\lambda_1, \lambda_2, \lambda_3)$. It has three independent parameters. For convenient physical information extraction, other three physical meaningful parameters are here suggested to replace the three eigenvalues, i.e. the total power SPAN, the scattering entropy H, and the anisotropy A

$$SPAN=\lambda_1+\lambda_2+\lambda_3 \quad (8)$$

$$H=-\sum_{i=1}^{3} p_i \log_3 p_i \text{ , with } p_i=\frac{\lambda_i}{\lambda_1+\lambda_2+\lambda_3} \quad (9)$$

$$A=\frac{\lambda_2-\lambda_3}{\lambda_2+\lambda_3}$$

The SPAN is the total power backscattered from the target, which was introduced by Cao *et al*. into the classification applications [15]. The entropy H is an indicator of the scattering randomness. The anisotropy A is also physical meaningful.

3.2. Model of the matrix U

As the matrix Λ has three DoFs, the matrix U has only six DoFs.

3.2.1. Model of the dominant eigenvector k_1

For three dimensional complex vector k_1, there are six DoFs. Two DoFs are lost because of 1) absolute phase indetermination and 2) unitary restriction [5]. Thus four independent parameters are used to model k_1.

We model k_1 using Touzi's TSVM as

$$k_1=\begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos 2\psi & -\sin 2\psi \\ 0 & \sin 2\psi & \cos 2\psi \end{bmatrix}\begin{bmatrix} \cos\alpha_s \cos 2\tau_m \\ \sin\alpha_s e^{j\Phi_{\alpha s}} \\ -j\cos\alpha_s \sin 2\tau_m \end{bmatrix}$$

$$=\begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos 2\psi & -\sin 2\psi \\ 0 & \sin 2\psi & \cos 2\psi \end{bmatrix}\begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{j\Phi_{\alpha s}} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} \cos 2\tau_m & 0 & -j\sin 2\tau_m \\ 0 & 1 & 0 \\ -j\sin 2\tau_m & 0 & \cos 2\tau_m \end{bmatrix}\begin{bmatrix} \cos\alpha_s & -\sin\alpha_s & 0 \\ \sin\alpha_s & \cos\alpha_s & 0 \\ 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

$$=SU(\psi)SU(\Phi_{\alpha s})SU(\tau_m)SU(\alpha_s)\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad (10)$$

The parameter ψ is the orientation angle of k_1. The parameter τ_m is the helix angle of k_1, which measures

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the asymmetry of the target represented by k_1. The parameter α_s is the scattering type magnitude, which is an important parameter used to discriminate the odd- and the even-bounce scatterings. The parameter $\Phi_{\alpha s}$ is the scattering type phase, which can be used to discriminate dipoles and quarter waves and has been used for ship recognition and other applications [4].

The alpha angle of Paladini ICTD is identical to the Cloude-Pottier alpha angle. But the Cloude-Pottier alpha angle is a mixer of alpha angle and helix angle, it is ambiguous in physical meaning [4]. The parameter α_s of TSVM or our ICTD can avoid such ambiguity.

The four parameters have clear physical meanings. They eliminate some ambiguities of the Cloude-Pottier alpha-beta model [4].

3.2.1. Model of the subdominant eigenvectors

As the matrix U has six DoFs, and the dominant eigenvector has four DoFs. Thus only two DoFs are left in the two subdominant eigenvectors k_2 and k_3.

After conducting the following unitary transformations, we can get [5]

$$X = SU(-\alpha_s)SU(-\tau_m)SU(-\Phi_{\alpha s})SU(-\psi)U = \begin{bmatrix} 1 & 0 & 0 \\ 0 & x_1 & x_2 \\ 0 & x_3 & x_4 \end{bmatrix}. \tag{11}$$

The subdominant eigenvectors are modelled by two unitary transformation matrices as follows

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & x_1 & x_2 \\ 0 & x_3 & x_4 \end{bmatrix} = SU(\Gamma)SU(\Psi) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-j2\Gamma} & 0 \\ 0 & 0 & e^{j2\Gamma} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos 2\Psi & -\sin 2\Psi \\ 0 & \sin 2\Psi & \cos 2\Psi \end{bmatrix}. \tag{12}$$

The parameter Ψ measures the relative magnitude of the second and third elements of the eigenvector, which is interpreted as the local orientation angle of the target. The parameter Γ introduces some phase difference containing the information of the local helix of the target. The physical basis of these two parameters needs further validation.

In [16], the last two parameters are interpreted as the "relative orientation" and "relative helicity", and they are both depolarization parameters.

In low entropy scattering situation, the dominant eigenvector described by four parameters accounts for the dominant or global scattering characteristics. The subdominant eigenvectors described by the remained two parameters account for the local scattering characteristics of the target. In high entropy scattering situation, the scattering power of the subdominant eigenvectors are comparable to that of the dominant eigenvector, and more information is contained in the last two parameters compared to the low entropy situation.

By the proposed ICTD, nine independent parameters are decomposed from the coherency matrix, i.e. SPAN, H, A, ψ, τ_m, α_s, $\Phi_{\alpha s}$, Ψ, and Γ. Thus the proposed ICTD can avoid the problem of PoP. All the decomposed parameters have explicit physical meanings.

4. EXPERIMENTAL RESULTS

In this section, RADARSAT-2 C-band PolSAR data of San Francisco Bay area are processed to demonstrate the inherent physical meanings of the nine decomposed parameters.

The data are in single-look complex format. A refined Lee filter is then applied to suppress the speckle and get the coherency matrix format data. Only a part of the scene is utilized.

The total power SPAN is shown in Fig. 1(a), as one can see, dihedrals with specular scattering usually have higher backscattered powers. The scattering entropy H is shown in Fig. 1(b), from which one can see that the park area and the oriented urban area with higher scattering randomness have higher entropy. The anisotropy A is shown in Fig. 1(c). For ocean area and urban area, the minimum eigenvalue is very small, and thus A is large. The orientation ψ of the dominant eigenvector is shown in Fig. 1(d), where the blue color area reasonably corresponds to the oriented urban area. The helix angle τ_m of the dominant eigenvector is shown in Fig. 1(e), where small value of helix angle is exhibited for the whole scene. The scattering type magnitude α_s is shown in Fig. 1(f), which is close to $\pi/2$ for urban area, while close to zero for ocean area. The scattering type phase $\Phi_{\alpha s}$ is shown in Fig. 1(g), which also contains physical information as addressed before. The local orientation Ψ is shown in Fig. 1(h), which is large for oriented urban area and park area because the sub-scatterers in the cell have diverse orientations. The local helix angle Γ is shown in Fig. 1(i), and it is noise generally.

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5. DISCUSSION

Similarities and differences of the Paladini ICTD and the proposed ICTD are addressed.

First, the similarities are 1) they both avoid the problem of PoP; 2) they are both serial (multiplicative) decompositions, while other common decompositions which are parallel (additive) decompositions. 3) the helix angles of both ICTDs have ambiguities. The helix angle cannot describe the asymmetry when α_s equals $\pi/2$ for proposed ICTD, while the helix angle cannot describe the asymmetry when alpha angle equals zero for Paladini ICTD.

Second, the differences are 1) our proposed ICTD bases on the frequently used coherency matrix T, while Paladini ICTD bases on the coherency matrix G; 2) the dominant eigenvector model for our ICTD is based on TSVM, and it eliminates the alpha angle ambiguity of Paladini ICTD;

6. CONCLUSION

A novel serial (multiplicative) ICTD of the coherency matrix is proposed with nine decomposed independent parameters obtained and all of them have explicit physical meanings. The proposed decomposition successfully avoids the problem of PoP. Real PolSAR data are processed to demonstrate the effectiveness of the proposed approach. The classification method based on these nine parameters is under study.

7. REFERENCE

[1] J. R. Huynen, "Phenomenological theory of radar targets," Ph.D. Dissertation, Delf University of Technology, Delft, The Netherland, 1970.

[2] D, Li. and Y. H. Zhang, "Unified Huynen Phenomenological Decomposition of Radar Targets and Its Classification Applications," *IEEE Trans. Geosci. Remote Sens.*, DOI: 10.1109/TGRS.2015.2464113 (In Press).

[3] S. R. Cloude and E. Pottier, "A review of target decomposition theorems in radar polarimetry," *IEEE Trans. Geosci. Remote Sens.*, vol. 34, no. 2, pp. 498-518, Mar. 1996.

[4] R. Touzi, "Target scattering decomposition in terms of roll-invariant target parameters," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 1, pp. 73-84, Jan. 2007.

[5] Paladini, L. R. Ferro-Famil, E. Pottier, M. Martorella, F. Berizzi, and E. Dalle Mese, ''Lossless and sufficient psi-invariant decomposition of random reciprocal target,'' *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 9, pp. 3487–3501, Sep. 2012.

[6] A. Freeman and S. L. Durden, "A three-component scattering model for polarimetric SAR data," *IEEE Trans. Geosci. Remote Sens.*, vol. 36, no. 3, pp. 963-973, May 1998.

[7] W. T. An, Y. Cui, and J. Yang, "Three-component model-based decomposition for polarimetric SAR data," *IEEE Trans. Geosci. Remote Sens.*, vol. 48, no. 6, pp. 2732-2739, Jun. 2010.

[8] Y. Yamaguchi, A. Sato, W. M. Boerner, R. Sato, and H. Yamada, "Four-component scattering power decomposition with rotation of coherency matrix," *IEEE Trans. Geosci. Remote Sens.*, vol. 49, no. 6, pp. 2251-2258, Jun. 2011.

[9] J. S. Lee, T. L. Ainsworth, and Y. Wang, "Generalized polarimetric model-based decompositions using incoherent scattering models," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 3, pp. 1705–1718, May 2014.

[10] S. W. Chen, X. S. Wang, S. P. Xiao, and M. Sato, "General polarimetric model-based decomposition for coherency matrix," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 3, pp. 1843–1855, Mar. 2014.

[11] J. J. van Zyl, M. Arii, and Y. Kim, "Model-based decomposition of polarimetric SAR covariance matrices constrained for nonnegative eigenvalues," *IEEE Trans. Geosci. Remote Sens.*, vol. 49, no. 9, pp. 1104–1113, Sep. 2011.

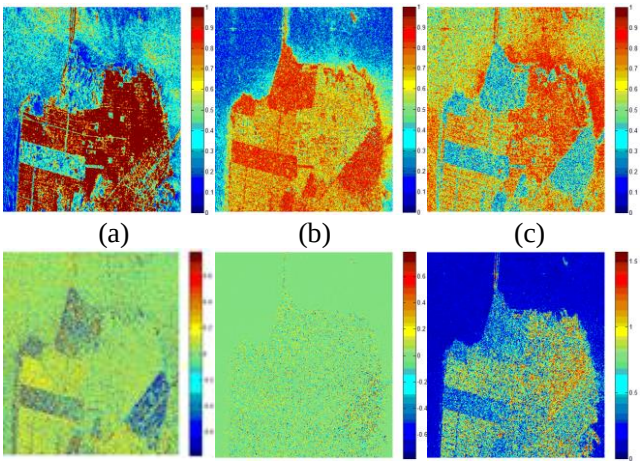
[12] Y. Cui, Y. Yamaguchi, J. Yang, H. Kobayashi, S. Park, and G. Singh, "On complete model-based decomposition of polarimetric SAR coherency matrix data," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 4, pp. 1991– 2001, Apr. 2014.

[13] C. L. Wang, W. D. Yu, R, Wang, Y. K. Deng, and F. J. Zhao, "Comparison of nonnegative eigenvalue decompositions with and without reflection symmetry assumptions," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 4, pp. 2278– 2287, Apr. 2014.

[14] J. R. Huynen, "Comments on target decomposition theorems," *in Direct and Inverse Methods in Radar Polarimetry*, W.-M. Boerner et al., Eds. Dordrecht, The Netherlands: Kluwer, 1992, pt. 1, pp. 387–399.

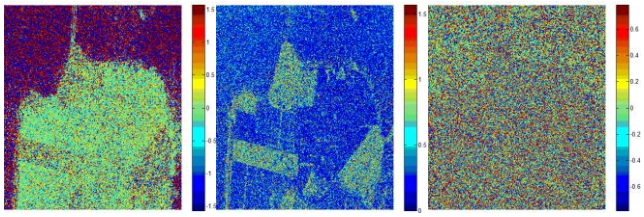
[15] F. Cao, W. Hong, Y. Wu, and E. Pottier, "An unsupervised segmentation with an adaptive number of clusters using the SPAN/H/alpha/A space and the complex wishart clustering for fully polarimetric SAR data analysis," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 11, pp. 3454–3467, Nov. 2007.

[16] T. L. Ainsworth, S. R. Cloude and J. S. Lee, "Eigenvector Analysis of Polarimetric SAR Data," Proceedings IGARSS'02, Toronto, 2002.



(a) (b) (c)

(d) (e) (f)



(g) (h) (i)

Figure. 1. Results of the parameters (a) SPAN, (b) H, (c) A, (d) ψ, (e) τ_m, (f) α_s, (g) $\Phi_{\alpha s}$, (h) Ψ, and (i) Γ.

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